Science of the Total Environment 665 (2019) 836–847

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

A hierarchical Bayesian model for decomposing the impacts of human activities and climate change on water resources in China

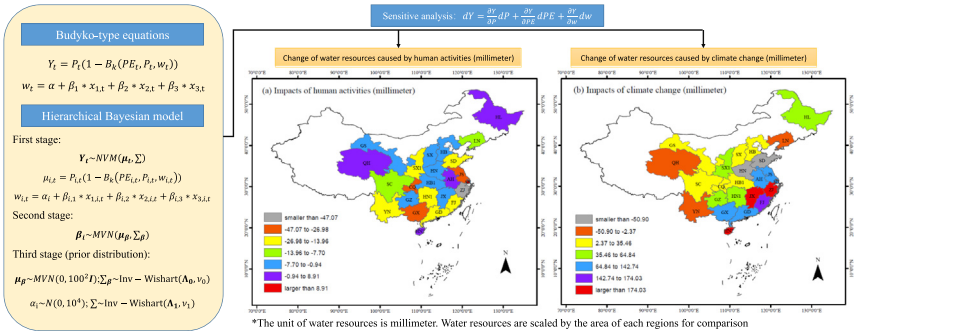
Xu Zhang [a], Qianjin Dong [a,b,*], Veber Costa [c], Xianxun Wang [a]

[a] State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan 430072, China
[b] The Research Institute for Water Security, Wuhan University, Wuhan 430072, China
[c] Department of Hydraulic and Water Resources Engineering, Federal University of Minas Gerais, Brazil

HIGHLIGHTS

- Budyko-type equations with time-varying parameters were verified in China.
- A hierarchical Bayesian model considering spatial correlation was established.
- Water resources decreased because of human activities for most regions of China.
- Climate change caused water resources to increase for most regions of China.

GRAPHICAL ABSTRACT


Budyko-type equations
$Y_t = P_t(1 - B_k(PE_t, P_t, w_t))$
$w_t = \alpha + \beta_1 * x_{1,t} + \beta_2 * x_{2,t} + \beta_3 * x_{3,t}$
Hierarchical Bayesian model
First stage:
$Y_t \sim NVM(\mu_t, \sum)$
$\mu_{i,t} = P_{i,t}(1 - B_k(PE_{i,t}, P_{i,t}, w_{i,t}))$
$w_{i,t} = \alpha_i + \beta_{i,1} * x_{1,i,t} + \beta_{i,2} * x_{2,i,t} + \beta_{i,3} * x_{3,i,t}$
Second stage:
$\beta_i \sim MVN(\mu_\beta, \sum_\beta)$
Third stage (prior distribution):
$\mu_\beta \sim MVN(0, 100^2 I); \sum_\beta \sim \text{Inv} - \text{Wishart}(\Lambda_0, \nu_0)$
$\alpha_i \sim N(0, 10^4); \sum \sim \text{Inv} - \text{Wishart}(\Lambda_1, \nu_1)$
Sensitive analysis: $dY = \frac{\partial Y}{\partial P}dP + \frac{\partial Y}{\partial PE}dPE + \frac{\partial Y}{\partial w}dw$
Change of water resources caused by human activities (millimeter)
Change of water resources caused by climate change (millimeter)
(a) Impacts of human activities (millimeter)
(b) Impacts of climate change (millimeter)
smaller than -47.07
-47.07 to -26.98
-26.98 to -13.96
-13.96 to -7.70
-7.70 to -0.94
-0.94 to 8.91
larger than 8.91
smaller than -50.90
-50.90 to -2.37
2.37 to 35.48
35.48 to 64.84
64.84 to 142.74
142.74 to 174.03
larger than 174.03
*The unit of water resources is millimeter. Water resources are scaled by the area of each regions for comparison

ARTICLE INFO

Article history:
Received 26 October 2018
Received in revised form 11 February 2019
Accepted 12 February 2019
Available online 13 February 2019

Editor: Ashantha Goonetilleke

Keywords:
Hierarchical Bayesian model
Budyko equation
Water resources management
Climate change
Human activities

ABSTRACT

Human activities and climate change are two key factors influencing the variation of the total amount of available surface and groundwater, hereafter termed water resources. Quantitatively separating their impacts remains a challenge. To this end, we used time-varying Budyko-type equations and a hierarchical Bayesian model in this paper to separate their impacts in 31 provincial-level divisions of China. The time-varying Budyko-type equations treat the Budyko equation parameter *w* as a variable, which depends on human activities (represented by per capita gross regional production) and climate change (represented by temperature and precipitation). The hierarchical model quantifies the uncertainty of parameters and the interrelation between covariates across regions in China. The results show that the time-varying Budyko-type equation can improve the fitting capability for water resources in China. The hierarchical Bayesian model, which considered spatial dependence, reduced the uncertainty of the parameters compared to spatially independent counterparts. For most regions of China, human activities reduce water resources while climate change increases them. Southeastern China is the most influenced area, and its water resources decreased approximately 50 mm because of human activities. This study can provide a basis for water resource management under climate change and human activity constraints in China.

© 2019 Elsevier B.V. All rights reserved.

1. Introduction

There is a large body of literature showing the impacts of human activities and climate change on the nonstationarity of regional water resources (Armal et al., 2018; Birsan et al., 2005; Jiang et al., 2015; Khaliq

* Corresponding author at: School of Water Resources and Hydropower Engineering, Wuhan University, Wuhan, Hubei Province 430072, China.
E-mail address: dqjin@whu.edu.cn (Q. Dong).

https://doi.org/10.1016/j.scitotenv.2019.02.189
0048-9697/© 2019 Elsevier B.V. All rights reserved.

et al., 2009; Kumar et al., 2009; Mccabe and Wolock, 2002). In effect, the traditional assumption of stationarity in the domains of flood frequency analysis and water resources management has faced serious challenges since hydrological time series increasingly exhibit time-varying statistical characteristics (Milly et al., 2008). Human activities are constantly changing topography, land use and vegetation cover, and these activities also directly affect the withdrawal of water from rivers or groundwater (Villarini et al., 2009; Villarini et al., 2012). Climate, in turn, alters precipitation and temperature patterns, which are the main factors that govern the long-term water balance in a given catchment (Alfieri et al., 2015; Boonwichai et al., 2018; Min et al., 2011).

The use of non-stationary models has been at the core of an intense debate in the hydrological scientific community. On the one hand, some authors, while acknowledging that the constantly changing climate and the intensification of human activities may have impacts on the water cycle, claim that our limited understanding of the physical processes underlying many atmospheric and hydrological phenomena prevents one to properly model them under non-stationary scenarios (Koutsoyiannis and Montanari, 2015; Lins and Cohn, 2011; Montanari and Koutsoyiannis, 2014). In effect, these authors reason that long-term characteristics of natural processes may not be suitably understood from the usually short hydrological time series available. In addition, the increased complexity in non-stationary models, which arises from their larger number of parameters, may entail considerably larger uncertainty in the estimates and is not explored and discussed in depth (Montanari and Koutsoyiannis, 2014; Serinaldi and Kilsby, 2015). Based on these facts, one might infer that a model with time-varying parameters should not be used unless the non-stationary characteristics of the process are well represented (Lins and Cohn, 2011).

On the other hand, some branches of research have focused on non-stationarity modeling strategies despite the incomplete understanding of its causes (Bracken et al., 2018; Lima et al., 2015; Sun et al., 2015; Villarini et al., 2009; Villarini et al., 2012). The rationale behind this approach is trying to account for the non-stationary characteristics of the physical process in order to improve estimation and prediction (Milly et al., 2008; Milly et al., 2015). This approach has become widespread since, due to the more complex structure of non-stationary models, gradual changes in climate and in the catchment may be accounted for and, thus, a reduction in estimation bias is likely to occur. Furthermore, the use of time-varying parameters makes the linkage with covariates potentially easier, which may also improve the fitting capability of a model (e.g., Jiang et al. (2015)). This line of reasoning constitutes the basis of our study, although we acknowledge that further research, particularly on the physical mechanisms triggering climate change, is necessary for providing more effective guidance on non-stationary hydrological modeling.

When nonstationary scenarios emerge, discerning the percentage of change in water resources that can be attributed to climate change or human activities is desirable, and constitutes the main objective of this study. A number of efforts have been made to investigate the relative contributions of these factors. Usual tools for this purpose are hydrological models (Ma et al., 2010; Wu et al., 2017b), water balance models (Zhang et al., 2016; Zuo et al., 2014), linear regression models (Ahn and Merwade, 2014; Kong et al., 2016), and Budyko-type equations (Donohue et al., 2011; Gao et al., 2016; Jiang et al., 2015; Mwangi et al., 2016; Roderick and Farquhar, 2011; Wu et al., 2017a; Xu et al., 2014; Zhang et al., 2011; Zhao et al., 2014). Hydrological models consider the physical mechanisms and estimate the influence of climate change and human activities over small time scales. However, such models usually require massive amounts of observed data, the calibration of parameters, and pose a variety of challenges for decomposing the impacts of climate change and human activities. Statistical methods (e.g., linear regression models) are relatively simple but lack a clear physical mechanism (Gao et al., 2016).

In contrast, Budyko-based methods are increasingly being used because of the simplicity of their calculations and the incorporation of water and energy constraints in hydrological processes (Gao et al., 2016; Greve et al., 2015; Gudmundsson et al., 2016; Singh and Kumar, 2015). Meanwhile, many studies provided a basis for decomposing the impacts of climate change and human activities using Budyko equations (Gao et al., 2016; Jiang et al., 2015; Roderick and Farquhar, 2011; Wu et al., 2017a; Xu et al., 2014; Zhang et al., 2011). Therefore, four kinds of Budyko-type equations were used in this study to decompose the impacts of climate change and human activities on the water resources of China. More specifically, we established an association between the parameter w in Budyko-type equations and yearly covariates such as population, per capita gross regional production (GRP), annual precipitation and mean annual temperature, then we used the sensitivity method to decompose the impacts of human activities and climate change.

Before application of Budyko-equations, the estimation of parameter w of Budyko-type equations is a critical challenge determining the accuracy of the results. The parameter w is a constant and usually interpreted as an integrative property (Zhang et al., 2004). A number of studies have been conducted to investigate the relationship of the parameter w to some factors such as topography, vegetation cover or soil property (Han et al., 2011; Jiang et al., 2015; Li et al., 2013; Yang et al., 2007; Zhang et al., 2004). However, unambiguous and conclusive physical or empirical associations to these factors are still not available in the present (Gudmundsson et al., 2016), indicating that large uncertain may contain in the framework of Budyko framework. Even though some studies have analyzed the uncertainty of Budyko-type equations by assigning a distribution to the parameter w of Budyko-type equations (Greve et al., 2015; Gudmundsson et al., 2016; Singh and Kumar, 2015), the uncertainty analyses of Budyko equations are still rare and ignore spatial correlations and interactions between covariates. Water resources in adjacent regions are frequently interrelated as a result of their similar climate conditions, economies and societies (Gudmundsson et al., 2016; Zhang et al., 2004). Ignorance of the spatial correlation in Budyko equations may decrease the reliability and robustness of the predictive results of Budyko equations.

To overcome this issue, we utilized a hierarchical Bayesian model to establish the Budyko-type equations. Hierarchical Bayesian models are powerful tools for modeling spatial correlation and the interactions between covariates to reduce uncertainty and have been used in many fields (Bracken et al., 2018; Kwon et al., 2008; Phung et al., 2018; Qian et al., 2014; Renard, 2011; Sun et al., 2015; Yan and Moradkhani, 2015; Yuan et al., 2017; Zeng et al., 2017). To the best of our knowledge, the hierarchical Bayesian framework has not been used in Budyko-type equations. Therefore, by combining the hierarchical Bayesian model with the Budyko-type equation, one may account for the spatial dependence of parameter w and thus provide a meaningful summary of the overall uncertainty.

In short, the main objectives that motivated this paper are 1) to assess the validity of Budyko-type equations with the time-varying parameter w in China; 2) to establish a hierarchical Bayesian model for Budyko-type equations to quantify the uncertainty and correlation of parameters; and 3) to decompose the impacts of human activities and climate change on water resources in China. First, we assessed the usefulness of Budyko-type equations with a constant parameter w and a time-varying parameter w for 31 provincial-level divisions of China. Then, a hierarchical model considering the spatial correlation of parameters and the interactions between covariates was established for the Budyko-type equations. The sensitivity method proposed by Roderick and Farquhar (2011) and Jiang et al. (2015) was then used to separate the impacts of climate change and human activities on water resources. Climate change factors (temperature and precipitation) and human activities factors (per capita GRP) are selected as the time-varying covariates explaining the variations of parameter w of the Budyko equation.

The organization of the paper is as follows. Section 2 introduces the data and the methods, including the Budyko-type equations, Bayesian models, and the decomposition method. Section 3 presents some results

of these experiments in China. Discussion and conclusions are provided in Section 4 and Section 5.

2. Materials and methods

2.1. Data

2.1.1. Hydrological and climatic data

Water resource data for 31 provincial-level divisions of China, from 2004 to 2016, were collected from the National Bureau of Statistics of China (http://data.stats.gov.cn/english/). The location of 31 provincial-level divisions in China is shown in Fig. S1, and their abbreviations are shown in Table S1. Here, water resources refer to the sum of surface water and groundwater. Surface water consists of the year by year renewable dynamic water resources, which exist in rivers, lakes and glaciers. In other words, the surface water is the natural runoff of rivers. Groundwater denotes the renewable dynamic water resources that exist in aquifers. To make water resources comparable for different regions, the water resources were scaled by the area of the provincial-level division; the unit of water resources used in this study is millimeters (mm).

Temperature and precipitation data were extracted from the GHCN Gridded V2 data and CPC Global Unified Precipitation data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA (https://www.esrl.noaa.gov/psd/). Both have a 0.5-degree latitude × 0.5-degree longitude global grid. The units of temperature and precipitation are centigrade and millimeters, respectively. Potential evaporation data are expressed as the pan evaporation in millimeters and were calculated from 824 meteorological stations provided by the China Meteorological Data Service Center (http://data.cma.cn/en).

2.1.2. Human activities data

Yearly observed population (10,000 persons), yearly per capita water consumption (m^3 per capita), and per capita GRP (10,000 yuan per capita) from 2004 to 2016 were collected from the National Bureau of Statistics of China (http://data.stats.gov.cn/english/) to represent human activities. To make covariates comparable for different regions, the population data was scaled by the area of the provincial-level division. The Spearman correlation coefficients between covariates and water resources were used to select correlated covariates. The results are presented in Table S2. Even though all three covariates are correlated with water resources, they are also internally correlated. Per capita GRP has the largest correlation with water resources. Therefore it was used as a covariate for explaining the influence of human activities.

2.2. Budyko-type equations

The water balance equation for a region, in a given year t, can be expressed as follows

$$Y_t = P_t - E_t - \Delta S \tag{1}$$

where Y_t is the water resource; P_t denotes the annual precipitation; E_t denotes the evaporation; and ΔS is the water storage change in the region. The water resources Y_t analyzed in this study contain not only surface water but also renewable groundwater that is replenished by local precipitation and surface water. In the long term, the water storage change in a region can be negligible, and ΔS is assumed to be null (Jiang et al., 2015; Xiong and Guo, 2012).

Precipitation P_t in a region can be observed by meteorological stations. Evaporation E_t, in turn, may be estimated by Budyko-type equations through considering the water and energy constraints in hydrological processes. Formally:

$$E_t = B_k(\Phi, w) * P_t \tag{2}$$

where Φ is the ratio of the potential evaporation PE_t to the precipitation P_t, which is usually termed the climatic dryness index; w is the parameter representing properties of a certain region. The equation originally proposed by Budyko (1974) does not contain the parameter w, but other studies have shown that the incorporation of such a parameter can improve estimation accuracy (Xiong and Guo, 2012). Resultingly, the Turc-Pike equation (Pike, 1964; Turc, 1954), the Fu equation (Fu, 1981; Zhang et al., 2004), the Zhang equation (Zhang et al., 2004), and the Wang-Tang equation (Wang and Tang, 2014), which are listed in Table 1, were used in this study to analyze the water balance in China.

To address the impacts of human activities and climate change on water resources, parameter w is expressed as a time-varying variable w_t with covariates $\boldsymbol{x_t} = (x_{1,t}, x_{2,t}, x_{3,t})$ (Jiang et al., 2015):

$$w_t = \alpha + \beta_1 * x_{1,t} + \beta_2 * x_{2,t} + \beta_3 * x_{3,t} \tag{3}$$

where $x_{1,t}$ is the per capita GRP representing the impacts of human activities; $x_{2,t}$ and $x_{3,t}$ are, respectively, the mean annual temperature and precipitation, thus representing climate change; α is the interception parameter; and $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3)$ is a vector with the regression coefficients necessary for estimation. The use of a time-varying model provides a way to account for not only the natural variability of the climatic dryness index but also for any possible changes of the Budyko curves utilized within the long-term water balance, which may implicitly reflect gradual changes in the catchment due to both climate and human activities (Jiang et al., 2015). In this paper, the models using constant parameter w are termed constant Budyko-type equations (CBE). In contrast, the models using time-varying variable w are termed time-varying Budyko-type equations (TVBE).

2.3. Bayesian model

This section incorporates the TVBE into a Bayesian paradigm to quantify the uncertainty of the parameters. First, a partial pooling model considering the geographic dependence was built under the framework of a hierarchical Bayesian model. For comparison, a spatially independent model where regression coefficients were independently estimated for a specific provincial-level division was also employed.

2.3.1. The partial pooling model

The partial pooling model considers the spatial correlation and the interactions between covariates in the framework of a hierarchical Bayesian model. The structure of the partial pooling model for n provincial-level divisions is as follows (Chen et al., 2014; Devineni et al., 2013; Wang et al., 2017):

First stage:

$$\boldsymbol{Y_t} \sim NVM\left(\boldsymbol{\mu_t}, \sum\right) \tag{4}$$

$$\mu_{i,t} = P_{i,t}\left(1 - B_k\left(PE_{i,t}, P_{i,t}, w_{i,t}\right)\right) \tag{5}$$

$$w_{i,t} = \alpha_i + \beta_{i,1} * x_{1,i,t} + \beta_{i,2} * x_{2,i,t} + \beta_{i,3} * x_{3,i,t} \tag{6}$$

Table 1
The four Budyko-type equations used in this study.

Budyko-type equation	Expression of Budyko-type equations
Turc-Pjke equation	$B_k(\Phi, w) = (1 + \Phi^{-w})^{-\frac{1}{w}}$
Fu equation	$B_k(\Phi, w) = 1 + \Phi - (1 + \Phi^{w})^{\frac{1}{w}}$
Zhang equation	$B_k(\Phi, w) = (1 + w\Phi)(1 + w\Phi + \Phi^{-1})^{-1}$
Wang-Tang equation	$B_k(\Phi, w) = \frac{[1 + \Phi - \sqrt{(1+\Phi)^2 - 4w(2-w)\Phi}]}{[2w(2-w)]}$

Second stage:

$$\boldsymbol{\beta_i} \sim MVN\left(\boldsymbol{\mu_\beta}, \sum\nolimits_{\beta}\right) \tag{7}$$

Third stage:

$$\boldsymbol{\mu_\beta} \sim MVN\left(0, 100^2\boldsymbol{I}\right) \tag{8}$$

$$\sum\nolimits_{\beta} \sim \text{Inv}-\text{Wishart}(\boldsymbol{\Lambda_0}, \nu_0) \tag{9}$$

$$\alpha_{\text{i}} \sim N\left(0, 10^4\right) \tag{10}$$

$$\sum \sim \text{Inv}-\text{Wishart}(\boldsymbol{\Lambda_1}, \nu_1) \tag{11}$$

The first stage is the likelihood function of the water resources. $\boldsymbol{Y_t}$ is a $n \times 1$ vector denoting the water resources of n provincial-level divisions at year t, and follows a multivariate normal distribution with hyperparameters $\boldsymbol{\mu_t}$ and $\sum$. Eq. (5) refers to the Budyko-type water balance equation, whereas Eq. (6) is the function of time-varying parameter $w_{i,\,t}$.

The second stage considers the correlation across provincial-level divisions and regression coefficients. The regression coefficients $\boldsymbol{\beta_i} = (\beta_{i,\,1}, \beta_{i,\,2}, \beta_{i,\,3})$ follow a common multivariate normal distribution with the hyperparameters $\boldsymbol{\mu_\beta}$ and $\sum_{\beta}$. $\boldsymbol{\mu_\beta}$ is a 3×1 vector representing the mean values of regression coefficients; $\sum_{\beta}$, in turn, is a 3×3 covariance matrix describing the joint variation between regression coefficients.

The third stage encompasses the prior distributions of the model parameters, and noninformative prior distributions were used for them. Parameter vector $\boldsymbol{\mu_\beta}$ follows a multivariate normal distribution with a mean value of zero and a covariance matrix of 100^2I, where $\boldsymbol{I}$ is a unit diagonal matrix. The prior distribution of the covariance matrix $\sum_{\beta}$ is defined as the inverse Wishart distribution, with scale matrix $\boldsymbol{\Lambda_0}$ and ν_0 degrees of freedom. In this study, the scale matrix $\boldsymbol{\Lambda_0}$ is diagonal, with elements equal to 0.0001. Parameter ν_0 is set as four, which is equal to one more than the dimensions of the matrix. The intercept parameter α_{i} follows a normal distribution with a mean value of zero and a standard deviation of 100. Finally, the covariate matrix $\sum$ follows an inverse Wishart distribution, with scale matrix $\boldsymbol{\Lambda_1}$ and ν_1 degrees of freedom. The scale matrix $\boldsymbol{\Lambda_1}$ is diagonal, with elements equal to 0.0001. Parameter ν_0 is set as $n + 1$, which is equal to one more than the dimension of the matrix.

2.3.2. The spatially independent model

A spatially independent model ignoring the spatial correlation between regions was also established to allow a comparison with the partial pooling model. Parameters of the spatially independent model are independently estimated for each region. The structure of the spatially independent model is as follows.

First stage:

$$Y_{i,t} \sim N\left(\mu_{i,t}, \sigma_i^2\right), i = 1, 2, \ldots, \text{n} \tag{12}$$

$$\mu_{i,t} = P_{i,t}\left(1-\text{B}_k\left(PE_{i,t}, P_{i,t}, w_{i,t}\right)\right) \tag{13}$$

$$w_{i,t} = \alpha_i + \beta_{i,1} * x_{1,i,t} + \beta_{i,2} * x_{2,i,t} + \beta_{i,3} * x_{3,i,t} \tag{14}$$

Second stage:

$$\boldsymbol{\beta_i} \sim MVN\left(\boldsymbol{0}, \boldsymbol{100^2 I}\right) \tag{15}$$

$$\alpha_{\text{i}} \sim N\left(0, 100^2\right) \tag{16}$$

$$\sigma_i^2 \sim \text{Inv}-Gamma(0.001, 0.001) \tag{17}$$

A Markov Chain Monte Carlo (MCMC) algorithm was used to simulate the posterior distributions of the parameters. Simulations were performed using "just another Gibbs sampler" (JAGS 4.3.0; (Denwood, 2016)). Three independent chains were simulated for the parameters. Each chain runs 500,000 cycles, and the last 10,000 are used for subsequent analyses.

2.4. Decomposition method

Previous studies have proposed methods based on the Budyko equation for decomposing the impacts of climate and human activities on water resources. Arora (2002) developed a comprehensive method based on the Budyko framework to analyze the impacts of long-term changes in potential evaporation and precipitation on changes in runoff. Wang and Hejazi (2011) analyzed the graphic characteristics of Budyko-type curves and proposed an approach to assess the impacts of human activities and climate change on runoff using Budyko-type equations. The sensitivity method proposed by Roderick and Farquhar (2011) has proven useful and has been extensively applied and explored (Jiang et al., 2015; Wu et al., 2017a; Xu et al., 2014; Zhang et al., 2011; Zhao et al., 2014). The rationale behind the decomposition method proposed by Roderick and Farquhar (2011) is that, by incorporating a parameter w to the originally proposed Budyko equation, the relative contributions of the referred intervenient factors may be estimated by segregating the influences of precipitation, evaporation and parameter w in the Budyko framework. In this sense, the changes in water resources caused by climate change would result from alterations in precipitation and evaporation. The changes in water resources caused by human activities, on the other hand, would stem from the variation in parameter w.

In this study, the total change in the water resource dY is estimated on the basis of the sensitivity method, which was proposed by Roderick and Farquhar (2011) and then modified by Jiang et al. (2015). Formally, by assuming a first order approximation, the incremental change in the total form in water resources may be expressed as:

$$dY = \frac{\partial Y}{\partial P}dP + \frac{\partial Y}{\partial PE}dPE + \frac{\partial Y}{\partial w}dw \tag{18}$$

where the differential change in the water resources dY is expressed by the sensitivity analysis. The partial derivatives on the right-hand side of the equation are the so-called sensitivity coefficients, which represent the change rate of each variable.

Let the water resources, precipitation, potential evaporation, and parameter w, in a given prechange period, be expressed as Y^0, P^0, PE^0, and w^0, respectively; similarly, let the referred quantities in the postchange period be expressed as Y^1, P^1, PE^1, and w^1, respectively. The changes of these parameters from the prechange period to the postchange counterpart are denoted by ΔY, ΔP, ΔPE and Δw, respectively. The change in the water resource ΔY, using the discretized forms of Eq. (18), can be then estimated as follows:

$$\begin{aligned}\Delta Y = Y^1 - Y^0 = &\frac{1}{2}\left(\frac{\partial Y^0}{\partial P^0} + \frac{\partial Y^1}{\partial P^1}\right)\Delta P + \frac{1}{2}\left(\frac{\partial Y^0}{\partial PE^0} + \frac{\partial Y^1}{\partial PE^1}\right)\Delta PE \\ &+ \frac{1}{2}\left(\frac{\partial Y^0}{\partial w^0} + \frac{\partial Y^1}{\partial w^1}\right)\Delta w\end{aligned} \tag{19}$$

where the first and the second terms of the right-hand side of the equation are the impacts of climate change caused by precipitation P and potential evaporation PE, and shortly denoted by ΔY^{c-1}. The third term of the equation represents the influence of parameter w. The change Δw can be divided into two parts, Δw^{h} and Δw^{c}, which are linked to human activities and climate change, respectively. Δw, Δw^{h}, and Δw^{c}

can be expressed as follows

$$\Delta w = \Delta w^h + \Delta w^c \tag{20}$$

$$\Delta w^h = \beta_1 * \Delta x_1 \tag{21}$$

$$\Delta w^c = \beta_2 * \Delta x_2 + \beta_3 * \Delta x_3 \tag{22}$$

where Δx_1 is the covariate change in per capita GRP; Δx_2 and Δx_3 are the covariate changes in temperature and precipitation.

In summary, the change in water resources consists of the impacts of climate change ΔY^c and human activities ΔY^h.

$$\Delta Y = \Delta Y^c + \Delta Y^h \tag{23}$$

The impacts of the climate change ΔY^c may be formally described by:

$$\Delta Y^c = \Delta Y^{c\_1} + \Delta Y^{c\_2} \tag{24}$$

where ΔY^{c_1} accounts for the first and the second term of the right-hand side of Eq. (19) and is expressed as:

$$\Delta Y^{c\_1} = \frac{1}{2}\left(\frac{\partial Y^0}{\partial P^0} + \frac{\partial Y^1}{\partial P^1}\right) * \Delta P + \frac{1}{2}\left(\frac{\partial Y^0}{\partial PE^0} + \frac{\partial Y^1}{\partial PE^1}\right)\Delta PE \tag{25}$$

whereas ΔY^{c_2} denotes the change in water resources caused by Δw^c and is given by:

$$\Delta Y^{c\_2} = \frac{1}{2}\left(\frac{\partial Y^0}{\partial w^0} + \frac{\partial Y^1}{\partial w^1}\right) * \Delta w^c = \frac{1}{2}\left(\frac{\partial Y^0}{\partial w^0} + \frac{\partial Y^1}{\partial w^1}\right) * (\beta_2 * \Delta x_2 + \beta_3 * \Delta x_3) \tag{26}$$

The impacts of the human activities ΔY^h are estimated by computing the influence of Δw^h.

$$\Delta Y^h = \frac{1}{2}\left(\frac{\partial Y^0}{\partial w^0} + \frac{\partial Y^1}{\partial w^1}\right)\Delta w^h = \frac{1}{2}\left(\frac{\partial Y^0}{\partial w^0} + \frac{\partial Y^1}{\partial w^1}\right) * \beta_1 * \Delta x_1 \tag{27}$$

3. Results

3.1. Validity of Budyko-type equations

The Budyko-type equations are useful tools for estimating long-term average annual evaporation (Zhou et al., 2015). However, their application may be somewhat limited due to the evaporation paradox described by Brutsaert and Parlange (1998). The study by Liu et al. (2009) has shown that the pan evaporation and actual evaporation exhibited opposing trends in Xinjiang province in the past half century. This phenomenon is not in accordance with the assumptions of the Budyko-type equations and may influence the inference process. Therefore, we first assessed the validity of the four Budyko-type equations in 31 provincial-level divisions in China. The least squares method was used to fit the CBE and TVBE. The Nash–Sutcliffe efficiency coefficient (NSE; Nash and Sutcliffe (1970)) was used to assess the results, which are summarized in Fig. 1.

Fig. 1 shows that the four kinds of Budyko-type equations in Table 1 exhibited very similar results for both constant and time-varying formulations, which is consistent with the study by Wu et al. (2017a). The provincial-level divisions whose *NSE* were larger than 0.5 for both situations are plotted in Fig. 2. Under CBE, there are 21 provincial-level divisions whose *NSE* are larger than 0.5. These divisions are mainly located in the east of China. The TVBE greatly improved the model's performance, and especially in some provincial-level divisions such as Shanxi (SX), Shaanxi (SX1), and Gansu provinces (GS). There are 27 provincial-level divisions whose *NSE* were larger than 0.5 using the TVBE, and these were retained for subsequent analysis.

The better performance of TVBE in this study can be, at least to some extent, explained as follows. First, nonstationary models contain more parameters and explanatory information. As a result, they are expected to provide more accurate estimates of the annual values of the water resources compared to their stationary counterpart. Nonetheless, it should be noted that this better performance occurs at the expense of greater complexity and uncertainty. Second, the water resources in many regions of China are correlated with per capita GRP, as shown in Table S2. The study by Min et al. (2011) shows that human activities influence precipitation extremes. The incorporation of per capita GRP as a covariate can, thus, provide additional explanatory information. Third, climate change may increase temperature and lead to more severe and frequent precipitation and floods (Wasko and Sharma, 2017; Yin et al., 2018). The TVBE models consider the influence of precipitation and temperature through the time-varying parameter w_t. The CBE, on the other hand, cannot consider the changing environmental conditions. The influence of temperature is only considered by the potential evaporation in CBE.

3.2. Comparison of Bayesian models

Before implementing the Bayesian model, we evaluated whether the water resources Y_t are normally distributed as assumed in Eqs. (4) and (12). Three steps were used for this purpose. First, Shapiro-Wilk tests (Shapiro and Wilk, 1965) at the 0.05 level of significance were applied to each provincial-level division to test the hypothesis of normality of water resources. In all regions, except for Tianjin (TJ), Inner Mongolia (NM), and Jilin (JL), the null hypothesis of the test could not be rejected. Thus, 24 regions were used for subsequent analysis. Second, we used the hierarchical cluster method to classify the 24 regions on the basis of mean precipitation and mean per capita GRP. Three clusters were identified using the "NbClust" package (Charrad et al., 2014) in R 3.4.4 (https://cran.r-project.org/web/packages/NbClust/). Results are shown in Fig. 3. The regions in one cluster have similar precipitation and per capita GRP, thereby indicating that the effects of human activities and climate change are similar in that cluster. Finally, three tests, (1) Henze-Zirkler's (Henze and Zirkler, 1990), (2) Mardia's (Mardia, 1970), and (3) Royston's (Royston, 1982) tests were used to verify the multivariate normality of water resources in regions of each cluster. All the tests indicate that the water resources in each cluster follow a multivariate normal distribution at the 0.05 level of significance. Partial pooling hierarchical Bayesian models, using the previously outlined TVBE, were then established for the three clusters.

The root-mean-square error (RMSE), the Nash–Sutcliffe efficiency coefficient (NSE; Nash and Sutcliffe (1970)) and the mean width of annual 90% credible intervals (CI) of the water resources were used to assess the performance of the four models. The median values of the parameter posterior distributions were used to calculate these indexes. The variations of such indexes across the study region are depicted in Fig. 4. One may notice that the four kinds of Budyko-type equations exhibited very similar performance. Overall, the hierarchical model using Wang-Tang equations presented the largest mean NSE (=0.772).

The posterior distributions of the regression parameters $\boldsymbol{\beta_i}$ of the partial pooling model, using the Wang-Tang equation, are shown in Fig. 5. Parameter $\beta_{i,\ 1}$, which accounts for per capita GRP, is positive for 79.1% of divisions. This indicates that the per capita GRP shows positive correlations with the variable *w*. The increase of the variable *w* will cause an increase in evaporation and, accordingly, a decrease in water resources. Therefore, the per capita GRP has negative associations with water resources.

The posterior distributions of the regression parameters $\boldsymbol{\beta_i}$ of the spatially independent model, also using the Wang-Tang equation, are plotted in Fig. 5 for comparison. In most cases, the uncertainty of the

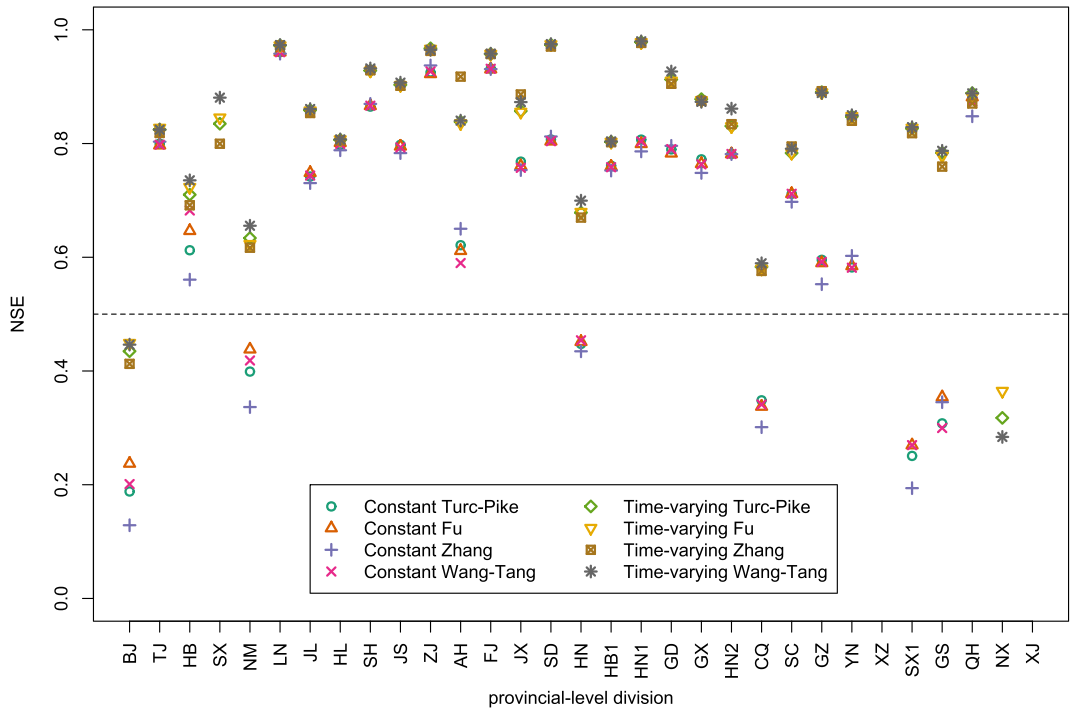


Fig. 1. *NSE* of Budyko-type equations for the set of 31 province-level divisions.

β_i parameters is relatively larger when compared to the partial pooling model. The variances of parameters $\beta_{i,1}$, $\beta_{i,2}$, and $\beta_{i,3}$ of the partial pooling model are smaller than those of their spatially independent counterparts in 83.3%, 91.6% and 91.6% of the provincial-level divisions, respectively. Moreover, the posterior distributions of the spatially independent model are more dispersed than those of the partial pooling counterpart, and a few outliers are verified for the former. For example, the parameters $\beta_{i,2}$ of the spatially independent model for Gansu (GS) and Chongqing (CQ) clearly depart from the parameters in other regions. Therefore, the partial model reduced the uncertainty of the parameters and increased the reliability of the parametric estimation by considering the spatial correlation.

3.3. Decomposition results

For decomposing the impacts of human activities and climate change on water resources, we utilized the median values of the posterior distributions of the partial pooling model (Jiang et al., 2015; Roderick and Farquhar, 2011). The first seven years period, which spanned from 2004 to 2010, is treated as the prechange period and will constitute the benchmark, whereas the final six years period, from 2011 to 2016, is treated as the postchange period. Thus, the data used in this study contain only 13 years of collection, spanning from 2004 to 2016. Even though it would be more appropriate to treat a larger time interval as the prechange period, the length of data restricts

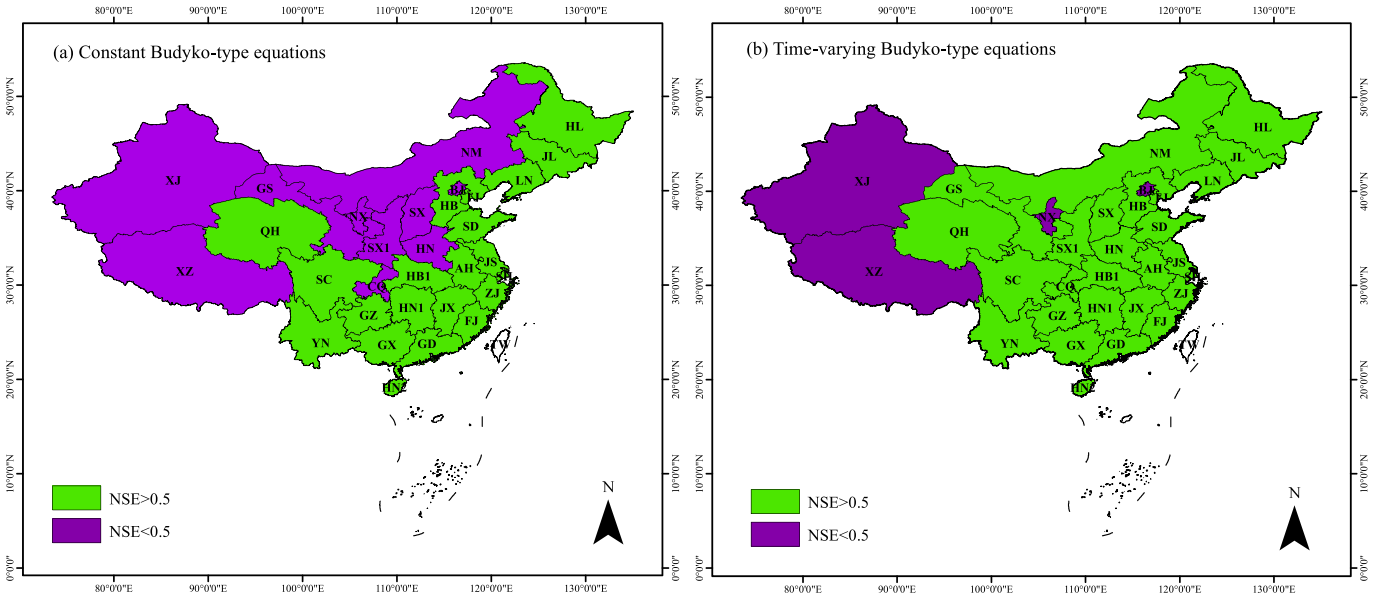


Fig. 2. Selected provincial-level divisions according to NSE values using CBE (a) and TVBE (b).

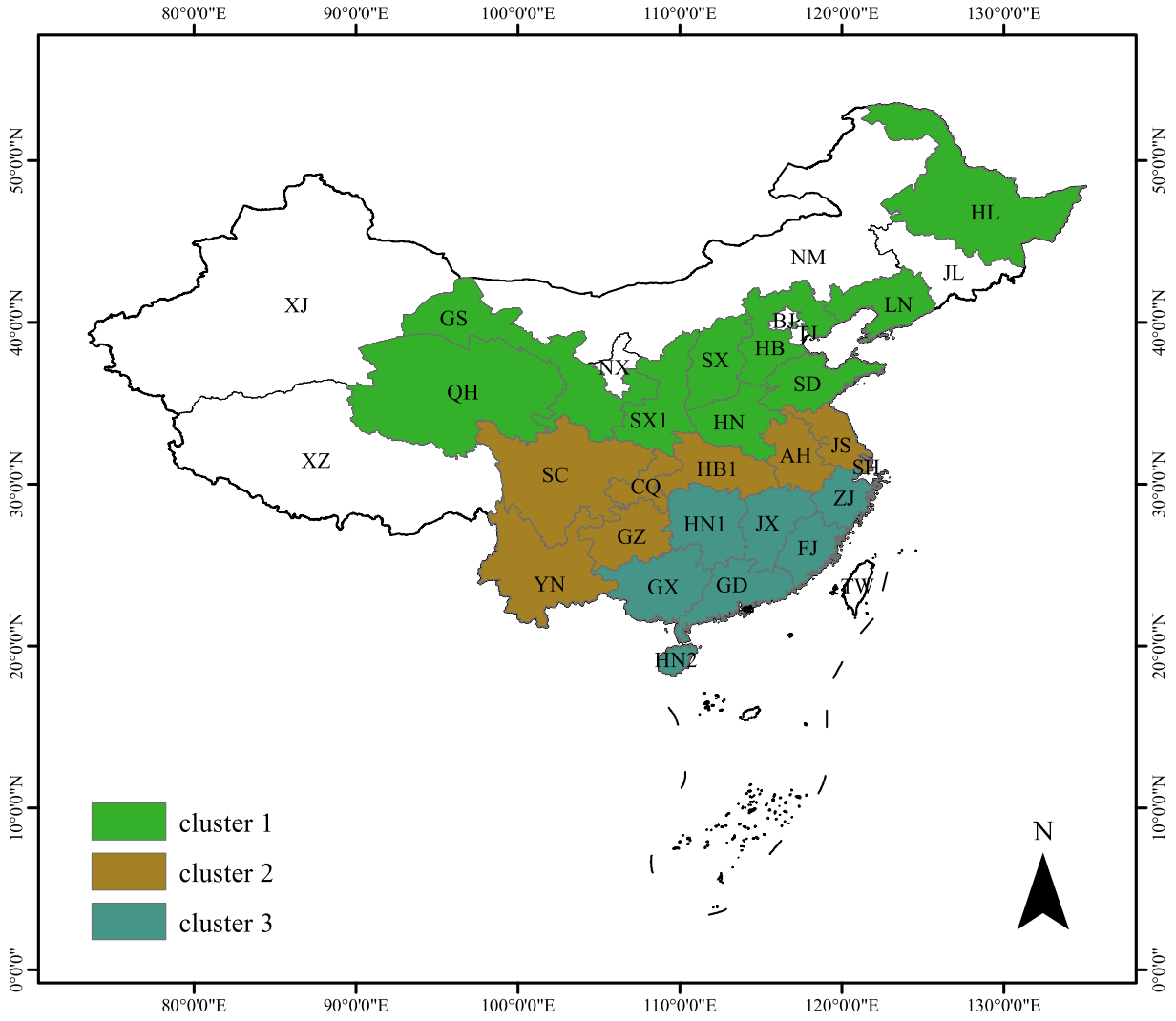


Fig. 3. Provincial-level divisions in three clusters.

our selection. To verify the decomposition method, the estimated and the observed change in water resources are plotted in Fig. 6. The estimated and the observed changes are close for most regions. To some extent, this points to the reliability of our decomposition method and results.

The decomposed impacts of human activities ΔY^h and climate change ΔY^c on the water resources of China are plotted in Fig. 7. The percentage of impacts of human activities ΔY^h and climate change ΔY^c on mean annual water resources are plotted in Fig. 8. The estimated ΔY^h were negative for most provincial-level divisions. The impacts of human activities ΔY^h were at their most intense in the southeast of China and reached approximately −50 mm in the Zhejiang (ZJ) province. The impacts of human activities gradually decrease towards the northwest and were virtually null in the Qinghai (QH) and Gansu (GS) provinces. These results are consistent with economic development patterns in China. In fact, higher levels of economic development are verified in the southeastern portion of the country, and an increased GRP will reduce the water resources based on the posterior distributions of $\beta_{i,1}$.

The estimated changes in water resources caused by climate change, ΔY^c, on the other hand, were positive for most regions. The regions with larger amounts of water resources in southeast China are more likely to be influenced by climate change. For most regions, the influence of climate change ranged from 2.37 mm to 64.84 mm. The percentage of the impacts of climate change on mean annual water resources exhibited obvious geographic characteristics. The upstream portion of the Yangtze River basin, mainly covering Sichuan (SC), Chongqing (CQ), Hubei (HB1), Guizhou (GZ) and Hunan (HN1), presented percentages ranging from 0.35 to 4.79. In contrast, the upstream portion of the Yellow River basin, mainly covering Gansu (GS), Shanxi (SX), Shaanxi (SX1), yielded percentages ranging 6.12 to 8.75. The Qinling Mountains splits these two regions. The downstream portion of the Yangtze River is the most influenced area by climate change, and the percentages in this area are larger than 8.75.

4. Discussion

In this study, Budyko-type equations using constant and time-varying parameters w were compared for 31 provincial-level divisions in China. In the TVBE, parameter w was calculated as a time-varying variable, which is correlated with some yearly factors such as per capita GRP, temperature and precipitation. The results show that TVBE improves the fitting capability for most provincial-level divisions in China. This improvement is reasonable because the TVBE contains more parameters and more explanatory information. Jiang et al. (2015) also analyzed the relationship between the time-varying parameter w and some explanatory variables such as precipitation, temperature, cultivated land area and irrigated area and obtained a similar

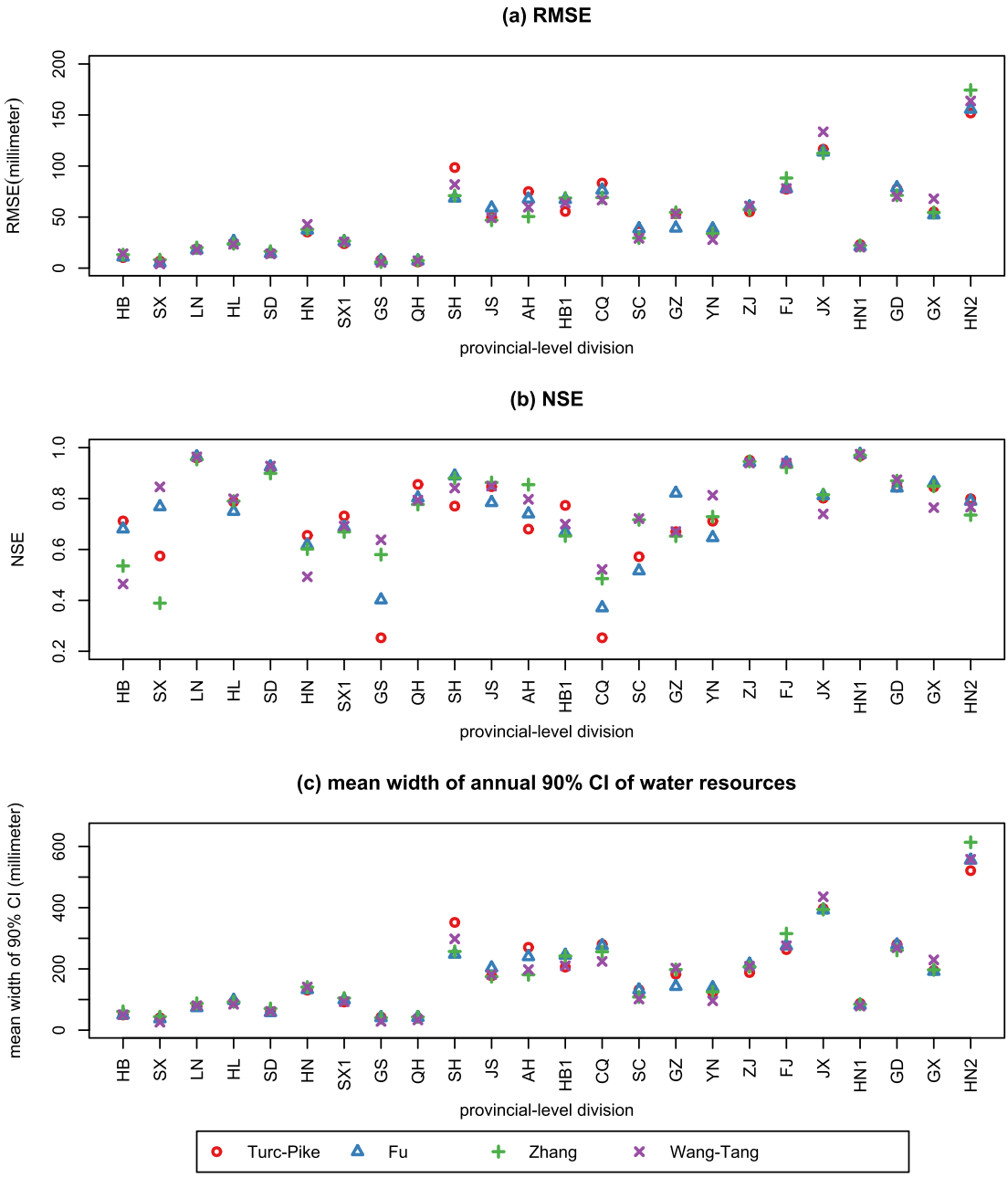


Fig. 4. *RMSE* (a), *NSE* (b), and mean width of the annual 90% CI of the water resources (c) of partial pooling Bayesian models using TVBE.

improvement in the Budyko-type equation. Overall, there are still many explanatory factors which may have significant associations with runoff or water resources and deserve further attention in future applications of TVBE.

The water resources analyzed in this study contain not only surface water but also ground water. However, most of the previous studies consulted in our literature review used runoff as their target, ignoring the influence of groundwater. Groundwater withdrawal in China has drastically increased in recent years due to economic development. We also tested the fitting capability of TVBE only for surface water, i.e., runoff. The NSE values declined by approximately 0.1 for some dry regions, compared to the NSE values for the water resources including renewable groundwater. The reasons for this improvement encompass two aspects. First, precipitation is not only converted into surface water and evaporation but it also replenishes the groundwater in aquifers. Therefore, the calculation of evaporation from Budyko-type equations becomes more accurate if incorporating renewable groundwater. Second, the groundwater level frequently changes over time because of human activities. By taking the renewable groundwater into consideration, the assumption that the water storage change ΔS in Eq. (1) is zero becomes more convincing.

A partial pooling hierarchical Bayesian model using TVBE was established in this study for quantifying uncertainty and the spatial correlation and interactions between regression parameters. The posterior distributions of the regression parameters β_i show that an increase in per capita GRP will decrease the water resources. In the future, the economy is expected to grow in China, thus suggesting that the water resources will continuously decrease in the country. Southeastern China is likely to be the most influenced region based on our decomposed results, and this may provide some guidance for water resources management in China.

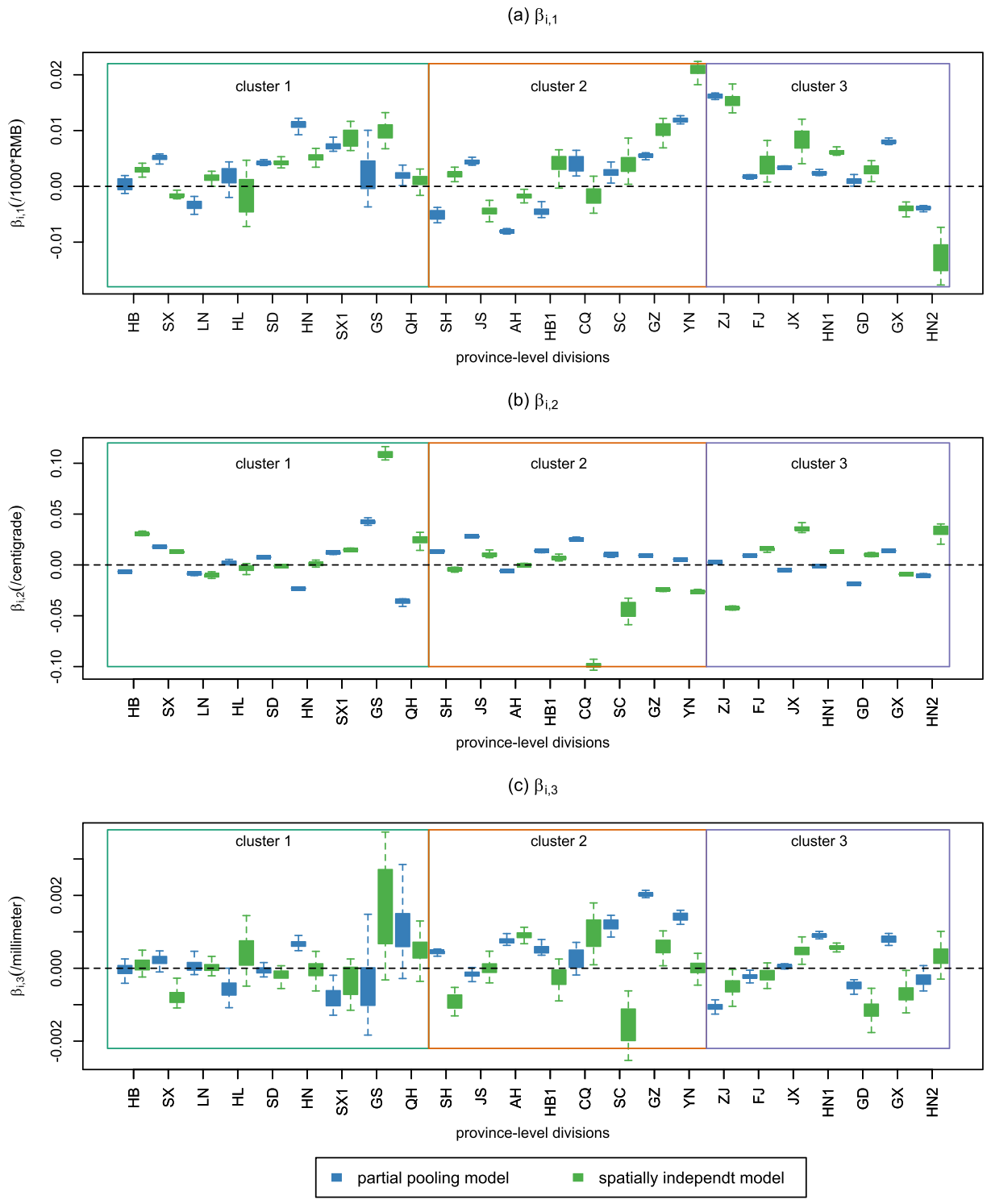


Fig. 5. Boxplots of posterior distributions of regression parameters $\beta_{i,1}$ (a), $\beta_{i,2}$ (b), and $\beta_{i,3}$ (c) of the partial pooling model and the spatially independent model, using the Wang-Tang Budyko-type equation.

Currently, nonstationarity has raised numerous discussions in hydrology. The results in this study favor the nonstationary assumptions of water resources in China. At least in this case, the TVBE exhibited a better performance than CBE. Human activities do have large impacts in China, especially in some developed regions. However, the incorporation of nonstationarity may also induce other problems. The complexity of the nonstationary model is higher than stationary ones. The increased number of parameters may also increase the uncertainty of the results. In addition, different authors have different methods addressing nonstationarity; thus, different results may be obtained. For example, this study selected per capita GRP to represent human activities, but other studies used surface temperature anomalies (Armal et al., 2018) or irrigation area (Jiang et al., 2015) to represent the influence of human activities. Additionally, although stationary models were outperformed by their nonstationary counterparts in this study, they can still be applied to most

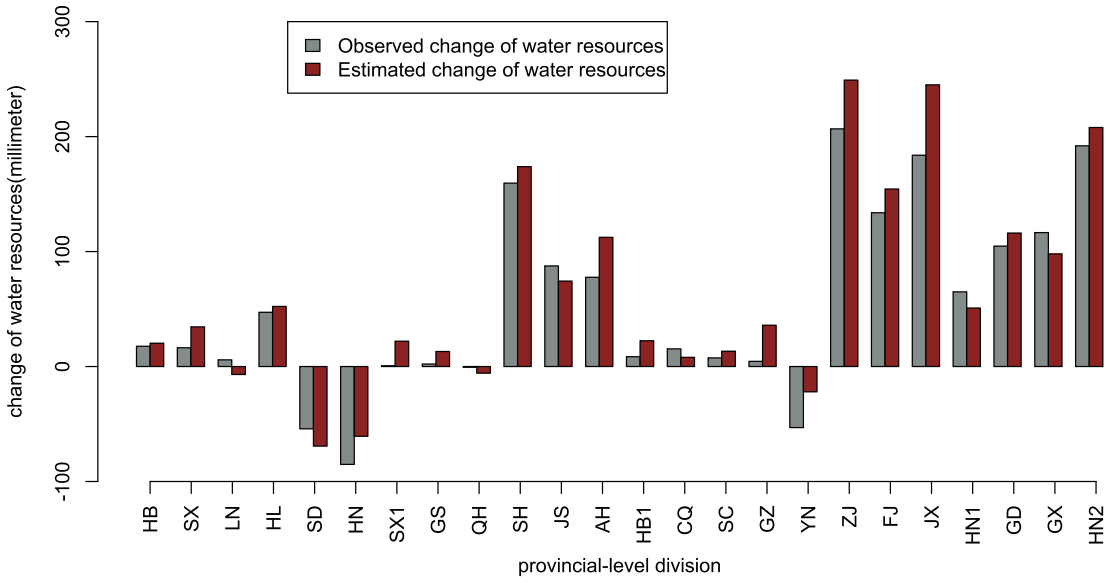


Fig. 6. Estimated change of water resources using sensitivity analysis and observed change of water resources for 27 provincial-level divisions.

regions in China. There are 21 provincial-level divisions whose *NSE* of stationary models are larger than 0.5, accounting for 68% of total divisions. Almost all scholars use the same method under the stationary assumption, and it have been used in the planning or the design of certain grand hydraulic engineering projects for many years. In summary, the stationary assumption method is acceptable in this study, but nonstationarity is a more appropriate method and still needs further investigation.

The main weakness of this study is that the length of data in the Bayesian model is short and only contains 13 years. To overcome this weakness, at least to some extent, a hierarchical Bayesian model considering spatial correlation was used to increase the reliability of the results. However, analyses using data spanning a longer period should be more convincing. Moreover, the intense influence of human activities in China started at least thirty years ago. The data in this study cannot entirely account for the impacts of human activities and climate change.

In closing, a few extensions of this study are presented. Here, the change in water resources was attributed to human activities and climate change. However, climate change actually contains two parts: climate variability and anthropogenic climate change (Armal et al., 2018). The climate variability is the climate's natural characteristics and can be represented by certain climate indexes such as the Interdecadal Pacific Oscillation (IPO), the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO), and the Atlantic Multidecadal Oscillation (AMO) (Gergis and Henley, 2017; Gershunov and Cayan, 2003). Anthropogenic climate change is the change of climatic conditions which does not emerge naturally and is caused by human activities (Cook et al., 2013). Therefore, decomposing the change in water resources into three parts would be more suitable, as it would include natural climate variability, anthropogenic climate change, and human activities. In the current framework of this study, separating the impacts of climate variability and anthropogenic climate change is difficult. With more investigations on climate variability and climate indexes, future works could

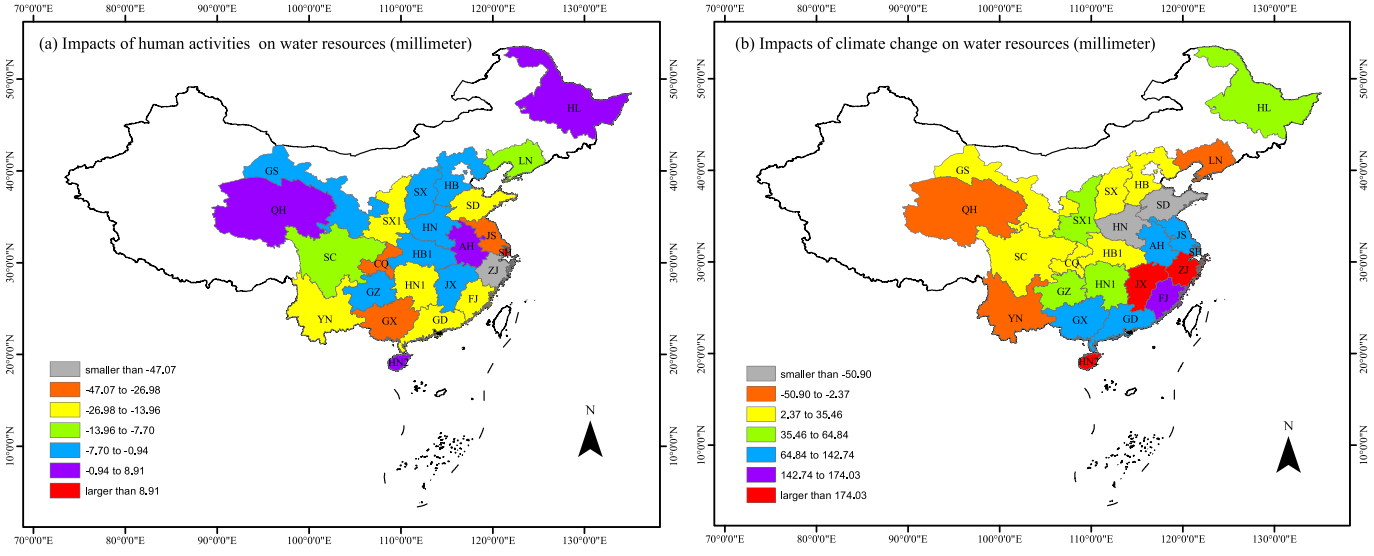


Fig. 7. Impacts of human activities (a) and climate change (b) on water resources of China.

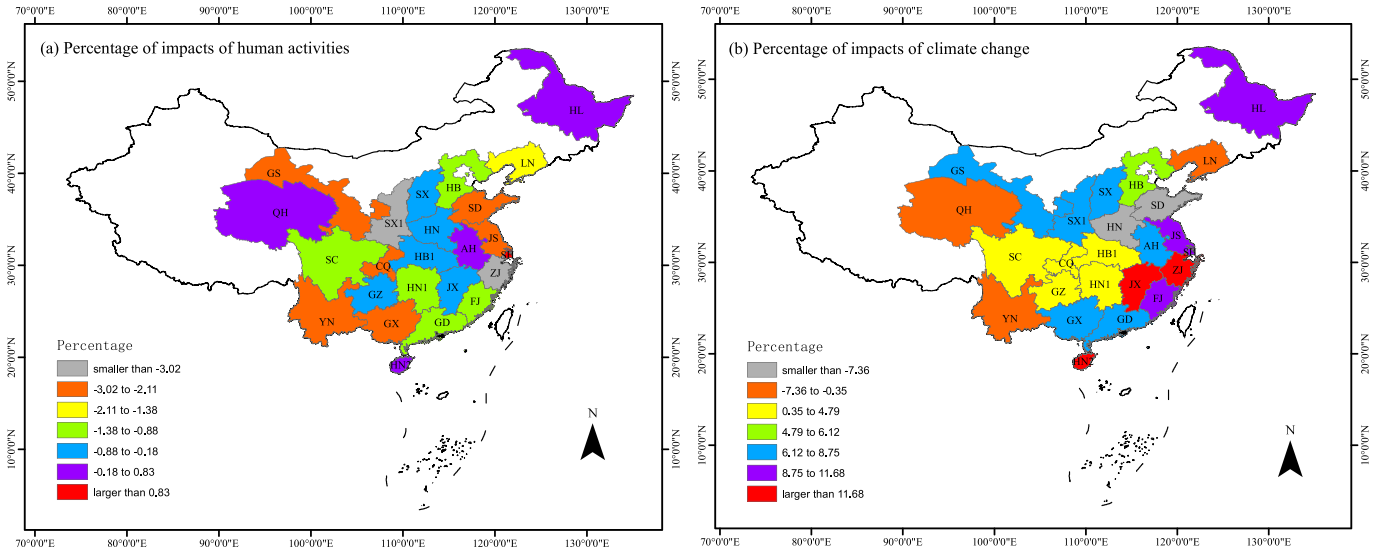


Fig. 8. Percentage of impacts of human activities (a) and climate change (b) to mean annual water resources in China.

make use of these variables to quantify the impacts of climate variability.

5. Conclusions

This study used a hierarchical Bayesian model for decomposing the impacts of human activities and climate change on water resources in China under a framework of Budyko-type equations. The Budyko-type equation parameter is no longer considered as a constant and correlates with the covariates of human activities and climate change. The main conclusions are as follows:

(1) Budyko-type equations using a time-varying parameter can improve the results, as compared to constant Budyko-type equations, for most regions in China. Moreover, four kinds of Budyko-type equations exhibited very similar performances, and the Wang-Tang equation was slightly better than the others.
(2) The hierarchical Bayesian model improves the parameters' estimation, as compared with the spatially independent model. The hierarchical Bayesian model not only reduced the uncertainty of the regression parameters but also reduced the number of outliers; thus, the reliability of the parametric estimation increased.
(3) Human activities decrease water resources for most provincial-level divisions in China. Southeastern China were the most influenced area and decreased approximately 50 mm. The impacts of human activities gradually decrease to the northwest and were virtually null in the Qinghai (QH) and Gansu (GS) provinces.
(4) The changes of water resources caused by climate change were positive for most divisions. The regions in southeast China are more likely to be influenced by climate change. In addition, the percentage of impacts of climate change on mean annual water resources exhibited obvious geographic characteristics. The upstream region of the Yangtze River basin and the upstream region of the Yellow River basin exhibited distinct patterns and they are split by the Qinling Mountains.

Acknowledgement

This research is financially supported by the National Key R&D Program of China (Grant No. 2016YFC0402708), National Nature Science Foundation of China (Grant Nos. 51439007, 91647119), and Innovation group of Hubei Natural Science Foundation (Grant No. 2017CFA015).

Conflict of interest

No conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.02.189.

References

Ahn, K.-H., Merwade, V., 2014. Quantifying the relative impact of climate and human activities on streamflow. J. Hydrol. 515, 257–266. https://doi.org/10.1016/j.jhydrol.2014.04.062.
Alfieri, L., Burek, P., Feyen, L., Forzieri, G., 2015. Global warming increases the frequency of river floods in Europe. Hydrol. Earth Syst. Sci. 19, 2247–2260. https://doi.org/10.5194/hess-19-2247-2015.
Armal, S., Devineni, N., Khanbilvardi, R., 2018. Trends in extreme rainfall frequency in the contiguous United States: attribution to climate change and climate variability modes. J. Clim. 31, 369–385.
Arora, V.K., 2002. The use of the aridity index to assess climate change effect on annual runoff. J. Hydrol. 265, 164–177.
Birsan, M.V., Molnar, P., Burlando, P., Pfaundler, M., 2005. Streamflow trends in Switzerland. J. Hydrol. 314, 312–329.
Boonwichai, S., Shrestha, S., Babel, M.S., Weesakul, S., Datta, A., 2018. Evaluation of climate change impacts and adaptation strategies on rainfed rice production in Songkhram River Basin, Thailand. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2018.10.201.
Bracken, C., Holman, K.D., Rajagopalan, B., Moradkhani, H., 2018. A Bayesian hierarchical approach to multivariate nonstationary hydrologic frequency analysis. Water Resour. Res. 54, 377–384.
Brutsaert, Amp W., Parlange, M.B., 1998. Hydrologic cycle explains the evaporation paradox. Nature 396 (30-30).
Budyko, M.I., 1974. Climate and Life. Academic Press, New York.
Charrad, M., Ghazzali, N., Boiteau, V., Niknafs, A., 2014. Nbclust: an R package for determining the relevant number of clusters in a data set. J. Stat. Softw. 61, 1–36.
Chen, X., Hao, Z., Devineni, N., Lall, U., 2014. Climate information based streamflow and rainfall forecasts for Huai River basin using hierarchical Bayesian modeling. Hydrol. Earth Syst. Sci. 18, 1539–1548. https://doi.org/10.5194/hess-18-1539-2014.
Cook, J., Nuccitelli, D., Green, S.A., Richardson, M., Winkler, B., Painting, R., et al., 2013. Quantifying the consensus on anthropogenic global warming in the scientific literature. Environ. Res. Lett. 8, 24024–24027.
Denwood, M.J., 2016. runjags: an R package providing Interface utilities, model templates, parallel computing methods and additional distributions for MCMC models in JAGS. J. Stat. Softw. 071, 1–25.
Devineni, N., Lall, U., Pederson, N., Cook, E., 2013. A tree-ring-based reconstruction of Delaware River basin streamflow using hierarchical Bayesian regression. J. Clim. 26, 4357–4374.
Donohue, R.J., Roderick, M.L., McVicar, T.R., 2011. Assessing the differences in sensitivities of runoff to changes in climatic conditions across a large basin. J. Hydrol. 406, 234–244. https://doi.org/10.1016/j.jhydrol.2011.07.003.

Fu, B., 1981. On the calculation of the evaporation from land surface. Chin. J. Atmos. Sci. 5, 23–31.
Gao, G., Fu, B., Wang, S., Liang, W., Jiang, X., 2016. Determining the hydrological responses to climate variability and land use/cover change in the Loess Plateau with the Budyko framework. Sci. Total Environ. 557-558, 331–342. https://doi.org/10.1016/j.scitotenv.2016.03.019.
Gergis, J., Henley, B.J., 2017. Southern Hemisphere rainfall variability over the past 200 years. Clim. Dyn. 48, 2087–2105. https://doi.org/10.1007/s00382-016-3191-7.
Gershunov, A., Cayan, D.R., 2003. Heavy daily precipitation frequency over the contiguous United States: sources of climatic variability and seasonal predictability. J. Clim. 16, 2752–2765.
Greve, P., Gudmundsson, L., Orlowsky, B., Seneviratne, S.I., 2015. Introducing a probabilistic Budyko framework. Geophys. Res. Lett. 42, 2261–2269. https://doi.org/10.1002/2015GL063449.
Gudmundsson, L., Greve, P., Seneviratne, S.I., 2016. The sensitivity of water availability to changes in the aridity index and other factors—a probabilistic analysis in the Budyko space. Geophys. Res. Lett. 43, 6985–6994. https://doi.org/10.1002/2016GL069763.
Han, S., Hu, H., Yang, D., Liu, Q., 2011. Irrigation impact on annual water balance of the oases in Tarim Basin, Northwest China. Hydrol. Process. 25, 167–174.
Henze, N., Zirkler, B., 1990. A class of invariant consistent tests for multivariate normality. Comput. Stat. 19, 3595–3617. https://doi.org/10.1080/03610929008830400.
Jiang, C., Xiong, L., Wang, D., Liu, P., Guo, S., Xu, C.Y., 2015. Separating the impacts of climate change and human activities on runoff using the Budyko-type equations with time-varying parameters. J. Hydrol. 522, 326–338.
Khaliq, M.N., Ouarda, T.B.M.J., Gachon, P., 2009. Identification of temporal trends in annual and seasonal low flows occurring in Canadian rivers: the effect of short- and long-term persistence. J. Hydrol. 369, 183–197.
Kong, D.X., Miao, C.Y., Wu, J.W., Duan, Q.Y., 2016. Impact assessment of climate change and human activities on net runoff in the Yellow River Basin from 1951 to 2012. Ecol. Eng. 91, 566–573. https://doi.org/10.1016/j.ecoleng.2016.02.023.
Koutsoyiannis, D., Montanari, A., 2015. Negligent killing of scientific concepts: the stationarity case. Hydrol. Sci. J. 60, 1174–1183. https://doi.org/10.1080/02626667.2014.959959.
Kumar, S., Merwade, V., Kam, J., Thurner, K., 2009. Streamflow trends in Indiana: effects of long term persistence, precipitation and subsurface drains. J. Hydrol. 374, 171–183.
Kwon, H.H., Brown, C., Lall, U., 2008. Climate informed flood frequency analysis and prediction in Montana using hierarchical Bayesian modeling. Geophys. Res. Lett. 35, L05404.
Li, D., Pan, M., Cong, Z., Zhang, L., Wood, E., 2013. Vegetation control on water and energy balance within the Budyko framework. Water Resour. Res. 49, 6550.
Lima, C.H.R., Lail, U., Troy, T.J., Devineni, N., 2015. A climate informed model for nonstationary flood risk prediction: application to Negro River at Manaus, Amazonia. J. Hydrol. 522, 594–602. https://doi.org/10.1016/j.jhydrol.2015.01.009.
Lins, H.F., Cohn, T.A., 2011. Stationarity: wanted dead or alive?1. J. Am. Water Resour. Assoc. 47, 475–480. https://doi.org/10.1111/j.1752-1688.2011.00542.x.
Liu, B., Ma, Z., Xu, J., Xiao, Z., 2009. Comparison of pan evaporation and actual evaporation estimated by land surface model in Xinjiang from 1960 to 2005. J. Geogr. Sci. 19, 120–130.
Ma, H., Yang, D.W., Tan, S.K., Bing, G., Hu, Q.F., 2010. Impact of climate variability and human activity on streamflow decrease in the Miyun Reservoir catchment. J. Hydrol. 389, 317–324.
Mardia, K.V., 1970. Measures of multivariate skewness and kurtosis with applications. Biometrika 57, 519–530. https://doi.org/10.1093/biomet/57.3.519.
Mccabe, G.J., Wolock, D.M., 2002. A step increase in streamflow in the conterminous United States. Geophys. Res. Lett. 29, 38-1–38-4.
Milly, P., Julio, B., Malin, F., Robert, M.H., Zbigniew, W.K., Dennis, P.L., et al., 2008. Stationarity is dead. Science 319, 573–574.
Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., et al., 2015. On critiques of "stationarity is dead: whither water management? ". Water Resour. Res. 51, 7785–7789. https://doi.org/10.1002/2015WR017408.
Min, S.K., Zhang, X., Zwiers, F.W., Hegerl, G.C., 2011. Human contribution to more-intense precipitation extremes. Nature. 470, 378–381.
Montanari, A., Koutsoyiannis, D., 2014. Modeling and mitigating natural hazards: stationarity is immortal! Water Resour. Res. 50, 9748–9756. https://doi.org/10.1002/2014wr016092.
Mwangi, H.M., Julich, S., Patil, S.D., Mcdonald, M.A., Feger, K.H., 2016. Relative contribution of land use change and climate variability on discharge of upper Mara River, Kenya. J. Hydrol. Reg. Stud. 5, 244–260.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — a discussion of principles. J. Hydrol. 10, 282–290. https://doi.org/10.1016/0022-1694(70)90255-6.
Phung, D., Chu, C., Tran, D.N., Huang, C., 2018. Spatial variation of heat-related morbidity: a hierarchical Bayesian analysis in multiple districts of the Mekong Delta region. Sci. Total Environ. 637-638, 1559–1565. https://doi.org/10.1016/j.scitotenv.2018.05.131.
Pike, J.G., 1964. The estimation of annual run-off from meteorological data in a tropical climate. J. Hydrol. 2, 116–123.
Qian, C., Yu, J.Y., Chen, G., 2014. Decadal summer drought frequency in China: the increasing influence of the Atlantic multi-decadal oscillation. Environ. Res. Lett. 9, 124004.
Renard, B., 2011. A Bayesian hierarchical approach to regional frequency analysis. Water Resour. Res. 47, W11513. https://doi.org/10.1029/2010WR010089.
Roderick, M.L., Farquhar, G.D., 2011. A simple framework for relating variations in runoff to variations in climatic conditions and catchment properties. Water Resour. Res. 47, 667–671.
Royston, J.P., 1982. An extension of Shapiro and Wilk-W test for normality to large samples. J. R. Stat. Soc.: Ser. C: Appl. Stat. 31, 115–124.
Serinaldi, F., Kilsby, C.G., 2015. Stationarity is undead: uncertainty dominates the distribution of extremes. Adv. Water Resour. 77, 17–36. https://doi.org/10.1016/j.advwatres.2014.12.013.
Shapiro, S.S., Wilk, M.B., 1965. An analysis of variance test for normality (complete samples). Biometrika 52, 591–611. https://doi.org/10.1093/biomet/52.3-4.591.
Singh, R., Kumar, R., 2015. Vulnerability of water availability in India due to climate change: a bottom-up probabilistic Budyko analysis. Geophys. Res. Lett. 42, 9799–9807. https://doi.org/10.1002/2015GL066363.
Sun, X., Lall, U., Merz, B., Dung, N.V., 2015. Hierarchical Bayesian clustering for nonstationary flood frequency analysis: application to trends of annual maximum flow in Germany. Water Resour. Res. 51, 6586–6601. https://doi.org/10.1002/2015wr017117.
Turc, L., 1954. The water balance of soils: relationship between precipitations, evaporation and flow. Ann. Agronomiques. 5, 491–569.
Villarini, G., Smith, J.A., Serinaldi, F., Bales, J., Bates, P.D., Krajewski, W.F., 2009. Flood frequency analysis for nonstationary annual peak records in an urban drainage basin. Adv. Water Resour. 32, 1255–1266.
Villarini, G., Smith, J.A., Serinaldi, F., Ntelekos, A.A., Schwarz, U., 2012. Analyses of extreme flooding in Austria over the period 1951 to 2006. Int. J. Climatol. 32, 1178–1192.
Wang, D., Hejazi, M., 2011. Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. Water Resour. Res. 47, 411–417.
Wang, D.B., Tang, Y., 2014. A one-parameter Budyko model for water balance captures emergent behavior in darwinian hydrologic models. Geophys. Res. Lett. 41, 4569–4577. https://doi.org/10.1002/2014gl060509.
Wang, S., Sun, X., Lall, U., 2017. A hierarchical Bayesian regression model for predicting summer residential electricity demand across the U.S.A. Energy. 140, 601–611.
Wasko, C., Sharma, A., 2017. Global assessment of flood and storm extremes with increased temperatures. Sci. Rep. 7, 7945.
Wu, J., Miao, C., Wang, Y., Duan, Q., Zhang, X., 2017a. Contribution analysis of the long-term changes in seasonal runoff on the Loess Plateau, China, using eight Budyko-based methods. J. Hydrol. 545, 263–275. https://doi.org/10.1016/j.jhydrol.2016.12.050.
Wu, J., Miao, C., Zhang, X., Yang, T., Duan, Q., 2017b. Detecting the quantitative hydrological response to changes in climate and human activities. Sci. Total Environ. 586, 328–337. https://doi.org/10.1016/j.scitotenv.2017.02.010.
Xiong, L., Guo, S., 2012. Appraisal of Budyko formula in calculating long-term water balance in humid watersheds of southern China. Hydrol. Process. 26, 1370–1378.
Xu, X., Yang, D., Yang, H., Lei, H., 2014. Attribution analysis based on the Budyko hypothesis for detecting the dominant cause of runoff decline in Haihe basin. J. Hydrol. 510, 530–540. https://doi.org/10.1016/j.jhydrol.2013.12.052.
Yan, H., Moradkhani, H., 2015. A regional Bayesian hierarchical model for flood frequency analysis. Stoch. Env. Res. Risk A. 29, 1019–1036.
Yang, D., Sun, F., Liu, Z., Cong, Z., Ni, G., Lei, Z., 2007. Analyzing spatial and temporal variability of annual water-energy balance in nonhumid regions of China using the Budyko hypothesis. Water Resour. Res. 43, 436–451.
Yin, J.B., Gentine, P., Zhou, S., Sullivan, S.C., Wang, R., Zhang, Y., et al., 2018. Large increase in global storm runoff extremes driven by climate and anthropogenic changes. Nat. Commun. 9, 10. https://doi.org/10.1038/s41467-018-06765-2.
Yuan, X.C., Sun, X., Lall, U., Mi, Z.F., He, J., Wei, Y.M., 2017. China's socioeconomic risk from extreme events in a changing climate: a hierarchical Bayesian model. Clim. Chang. 139, 1–13.
Zeng, H., Sun, X., Lall, U., Feng, P., 2017. Nonstationary extreme flood/rainfall frequency analysis informed by large-scale oceanic fields for Xidayang Reservoir in North China. Int. J. Climatol. 37, 3810–3820. https://doi.org/10.1002/joc.4955.
Zhang, L., Hickel, K., Dawes, W.R., Chiew, F.H.S., Western, A.W., Briggs, P.R., 2004. A rational function approach for estimating mean annual evapotranspiration. Water Resour. Res. 40, 1–14. https://doi.org/10.1029/2003wr002710.
Zhang, Y., Guan, D., Jin, C., Wang, A., Wu, J., Yuan, F., 2011. Analysis of impacts of climate variability and human activity on streamflow for a river basin in Northeast China. J. Hydrol. 410, 239–247. https://doi.org/10.1016/j.jhydrol.2011.09.023.
Zhang, Q., Liu, J.Y., Singh, V.P., Gu, X.H., Chen, X.H., 2016. Evaluation of impacts of climate change and human activities on streamflow in the Poyang Lake basin, China. Hydrol. Process. 30, 2562–2576. https://doi.org/10.1002/hyp.10814.
Zhao, G., Tian, P., Mu, X., Jiao, J., Wang, F., Gao, P., 2014. Quantifying the impact of climate variability and human activities on streamflow in the middle reaches of the Yellow River basin, China. J. Hydrol. 519, 387–398. https://doi.org/10.1016/j.jhydrol.2014.07.014.
Zhou, G., Wei, X., Chen, X., Zhou, P., Liu, X., Xiao, Y., et al., 2015. Global pattern for the effect of climate and land cover on water yield. Nat. Commun. 6 (40-40).
Zuo, D.P., Xu, Z.X., Wu, W., Zhao, J., Zhao, F.F., 2014. Identification of streamflow response to climate change and human activities in the Wei River Basin, China. Water Resour. Manag. 28, 833–851. https://doi.org/10.1007/s11269-014-0519-0.